

CSC-466

# Analyzing Political Committee Election Donations



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# Why should you care?

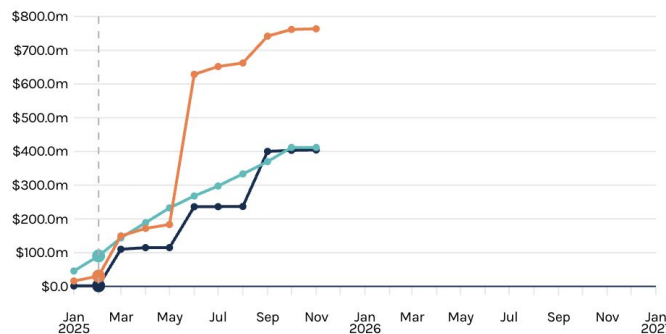
- We consistently see records broken with spending amounts in recent years, whether that's with each of the recent presidential cycles or with competitive congressional races (source: [OpenSecrets](#))
- News media coverage often focuses on press conferences, public statements, and political debates, but the increasing amount of money in politics may be more indicative of the policy decisions politicians make compared to generic politician rhetoric
- Analyzing political contributions data and understanding who funds your representatives provides us insights that aren't displayed publicly very often

## Dataset Overview

- Stanford DIME dataset (Database on Ideology, Money in Politics, and Elections)
- Includes contributions from individuals and various committees (PACs, Super PACs, etc.) to political candidates (state, federal, presidential elections)
- To narrow the scope (and use a manageable number of records), I chose to focus on donations from committees to federal congressional races
- Goal: predict which committees will donate to a candidate in the future, based on data midway through the election cycle
- Does not analyze spending, but notable that committees often spend large on behalf of candidates

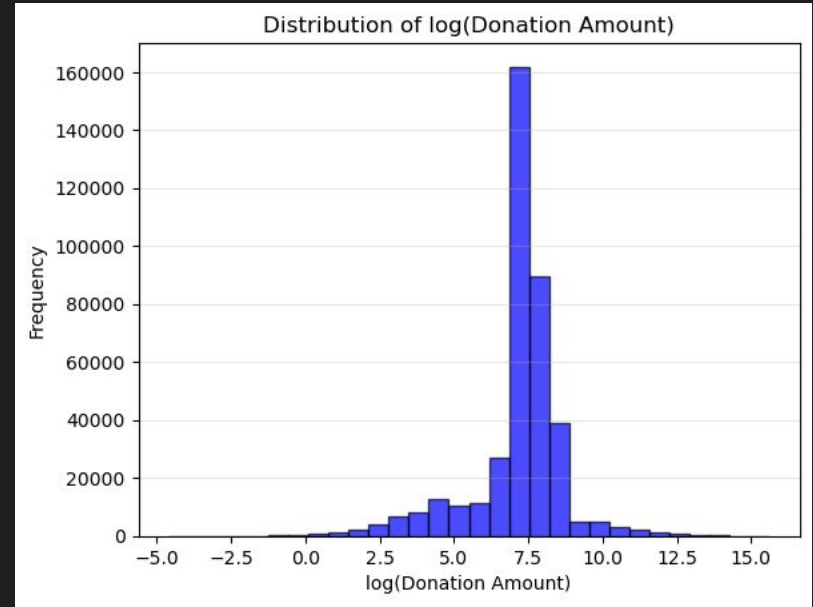
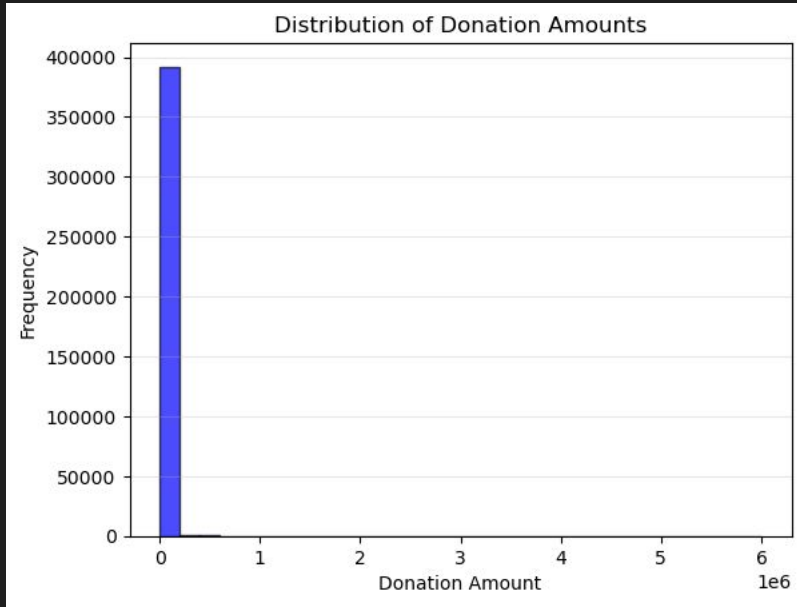
HOW MUCH MONEY HAS BEEN SPENT BETWEEN:

01/01/2025 - 02/28/2025

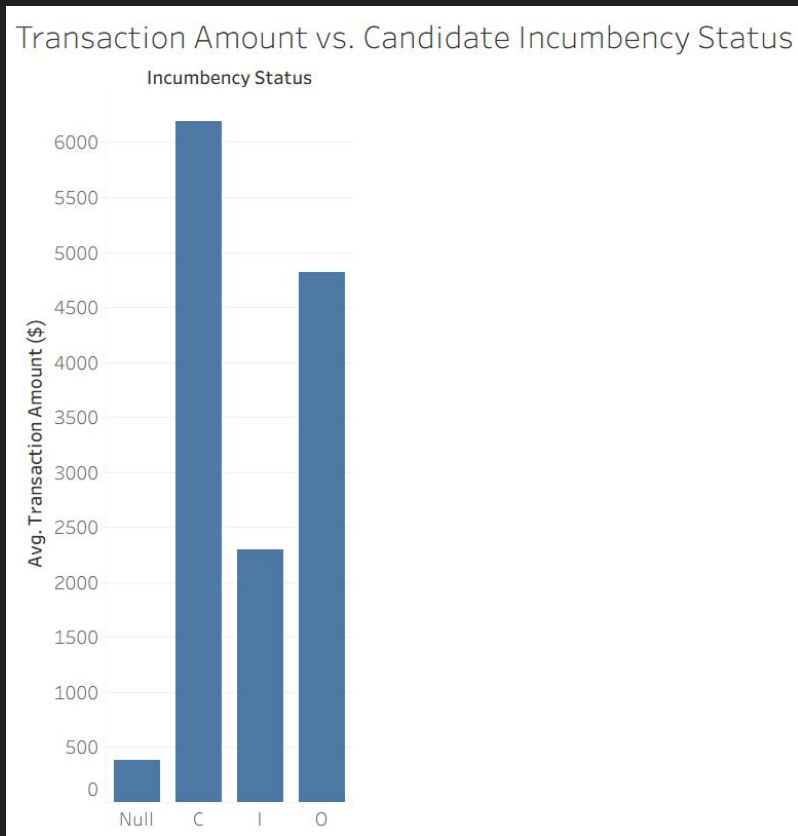


|                  |               |
|------------------|---------------|
| Candidates       | \$172,490     |
| PACs             | \$30,488,588  |
| Party committees | \$90,153,950  |
| All committees   | \$122,367,028 |

# Exploratory Data Analysis



# Exploratory Data Analysis



# Models

- Heuristic: for each committee, categorize them by party based on which party they donate the most to, then predict donors for each candidate as the committees that donate the most to
- Compared heuristic and random baselines to the following models:



## Surprise Collaborative Filtering w/ SVD

Used min-max scaling on committee vectors to get “ratings” from donation amounts, then generate “recommendations” from interaction matrix with surprise (SVD).

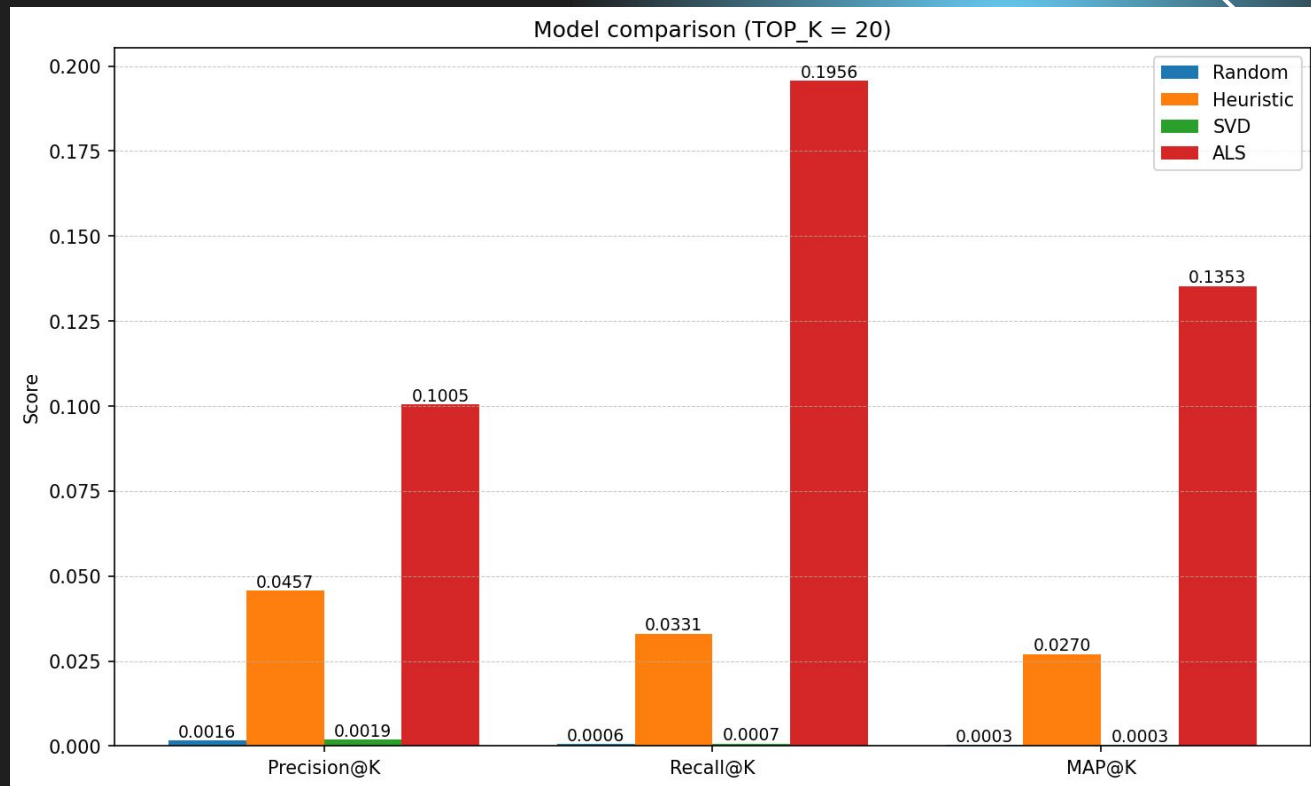
## Collaborative Filtering w/ ALS

Alternating Least Squares (ALS) is a model-based collaborative filtering algorithm that extracts latent feature vectors and is often used with implicit ratings.


## Random Forest

Using features about committees and candidates, predict a donation amount for each committee/candidate pair, and sort predicted donation amounts to get recommendations.

# Results



# Next Steps



## Step 1

Spend more time feature engineering and experimenting with the random-forest model (and potentially XGBoost).

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## Step 2

Spend more time on EDA or ML techniques to determine feature importance of features used.

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## Step 3

Improve the ALS collaborative filtering model using a hybrid model with committee/candidate features.





**Thank you!**